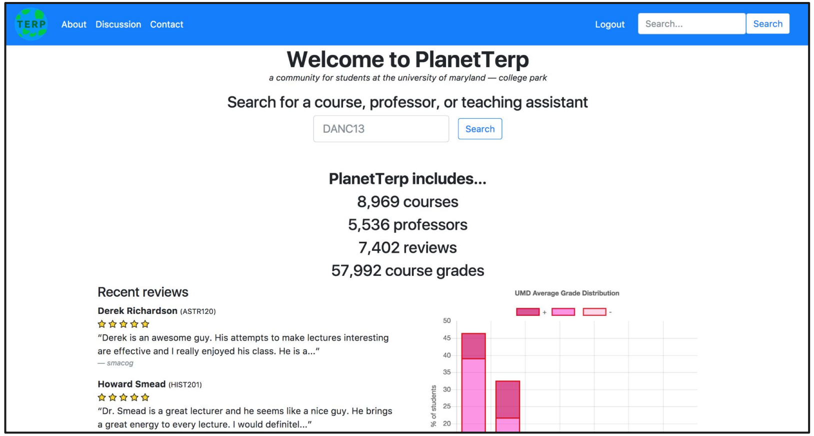
Predicting Professor Ratings Using Machine Learning

Planet Terp Overview

Planet Terp is a website where University of Maryland students can rate their professors and share experiences through reviews.

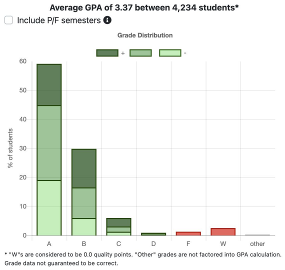
It's a useful resource for students to decide which professors to take based on ratings and reviews.

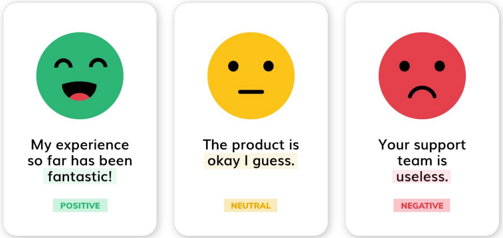


Why is this Problem Interesting?

Accurately predicting professor ratings can help students make more informed decisions.

This problem is interesting because it predicts a professor’s star rating using a combination of objective features like GPA and expected grades, along with subjective insights from sentiment analysis, instead of relying solely on students' star ratings.





Data Collection

Collected professor data (names, grades, reviews) and aggregated review data through the Planet Terp API.

Compiled data size of 3,000+ professors and 8,000+ reviews for training.

Cleaned and processed the data by removing missing values, making it ready for regression modeling.

Features Used for Prediction:

- Average GPA: The average GPA of students in the professor's classes.
- Average Expected GPA: The GPA students expect to achieve based on their reviews of the professor.
- Sentiment: A score derived from sentiment analysis of student reviews, indicating positive or negative sentiment.

Target Variable: Star Rating (average from 0–5 scale reviews)

Models Used

1. Linear Regression: A simple model to predict the professor rating based on linear relationships between features and the target.

2. Random Forest Regression: A learning method that uses multiple decision trees to reduce overfitting and improve predictions.

3. SVM (Support Vector Machine): More specifically Support Vector Regression, a numerical method that divides data based on the maximum margin hyperplane and focuses on predicting continuous output values rather than classifying data points

Training Process

1. Split the data into training and testing sets using a 80/20 split.

2. Trained each model using the training data and validated using 10-fold cross-validation.

Model Evaluation

Evaluation Metrics:

- Mean Squared Error (MSE): Measures how close the model's predictions are to the actual ratings. A lower MSE indicates better performance.
- Cross-Validation: 10-fold cross-validation was used to ensure the results were robust and not overfitted to a particular subset of data.

Results:

- Linear Regression: MSE = 0.5104
- Random Forest Regression: MSE = 0.5397
- SVM: MSE = 0.5008

Conclusion

Overall, the SVM model performed the best, achieving the lowest Mean Squared Error (MSE) among the models tested. Models were evaluated using 10-fold cross-validation, with MSE as the performance metric — where lower values indicate better predictions.

Feature importance was measured using the Random Forest model, revealing that sentiment from student reviews was the most influential factor, followed by average GPA and expected GPA.

Combining sentiment analysis with historical GPA data proved effective for accurately predicting professor star ratings.

Results:

- Linear Regression: MSE = 0.5104
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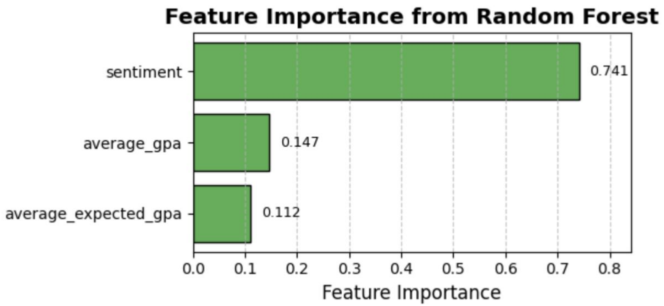

Imports

```
import requests
import json
import time
import random
import csv
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR

import numpy as np

!pip install vaderSentiment

Requirement already satisfied: vaderSentiment in
/usr/local/lib/python3.11/dist-packages (3.3.2)
Requirement already satisfied: requests in
/usr/local/lib/python3.11/dist-packages (from vaderSentiment) (2.32.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.11/dist-packages (from requests-
>vaderSentiment) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.11/dist-packages (from requests-
>vaderSentiment) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.11/dist-packages (from requests-
>vaderSentiment) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests-
>vaderSentiment) (2025.1.31)
```

API calls for professor info + reviews

```
profs = {}
offset = 0
batch_size = 100

while True:
    response = requests.get(
        f"https://planetterp.com/api/v1/professors?
reviews=true&type=professor&limit={batch_size}&offset={offset}"
    )
    profs_data = response.json()
```

```
    if not profs_data:
        break

    for prof_data in profs_data:
        if prof_data["average_rating"] == None:
            continue

        name = prof_data["name"]
        to_add = {
            "slug": prof_data["slug"],
            "type": prof_data["type"],
            "courses": prof_data["courses"],
            'average_rating': prof_data["average_rating"],
            "reviews": prof_data["reviews"]
        }
        profs[name] = to_add

    offset += batch_size

# Save the full file after scraping
with open("professors.json", "w", encoding="utf-8") as f:
    json.dump(profs, f, indent=2)
```

API calls for grades - calculate average GPA for each professor base on past grades

```
def calculate_average_gpa(grade_data):
    gpa_values = {
        'A+': 4.0, 'A': 4.0, 'A-': 3.7,
        'B+': 3.3, 'B': 3.0, 'B-': 2.7,
        'C+': 2.3, 'C': 2.0, 'C-': 1.7,
        'D+': 1.3, 'D': 1.0, 'D-': 0.7,
        'F': 0.0
    }

    total_points = 0.0
    total_students = 0

    for section in grade_data:
        for grade, value in gpa_values.items():
            count = section.get(grade, 0)
            total_points += count * value
            total_students += count

    if total_students == 0:
        return None  # Avoid division by zero

    average_gpa = total_points / total_students
    return round(average_gpa, 3)
```

```python
with open('professors.json', 'r') as f:
    professor_data = json.load(f)

results = []

for name in professor_data.keys():
    try:
        url = f"https://planetterp.com/api/v1/grades?professor={name}"
        response = requests.get(url)
        response.raise_for_status()
        grades_data = response.json()

        avg_gpa = calculate_average_gpa(grades_data)
        results.append({
            "name": name,
            "average_gpa": avg_gpa
        })


    except Exception as e:
        print(f"Failed for {name}: {e}")
        results.append({
            "name": name,
            "average_gpa": None
        })

print(f"Number of average gpa calculated: {len(results)}")


# Save results
with open('professors_with_avg_gpa.json', 'w') as f:
    json.dump(results, f, indent=2)
```

```
Number of average gpa calculated: 4211
```

Compute Average GPA and Expected GPA

```python
gpa_values = {
    'A+': 4.0, 'A': 4.0, 'A-': 3.7,
    'B+': 3.3, 'B': 3.0, 'B-': 2.7,
    'C+': 2.3, 'C': 2.0, 'C-': 1.7,
    'D+': 1.3, 'D': 1.0, 'D-': 0.7,
    'F': 0.0
}

# Compute average expected GPA from reviews
def calculate_average_expected_gpa(reviews):
    total = 0.0
    count = 0
```

```
    for review in reviews:
        expected = review.get("expected_grade", "")
        if expected in gpa_values:
            total += gpa_values[expected]
            count += 1
    if count == 0:
        return None
    return round(total / count, 3)

# Load professor data
with open('professors.json', 'r') as f:
    professors = json.load(f)

# Load precomputed average GPA data
with open('professors_with_avg_gpa.json', 'r') as f:
    avg_gpa_data = json.load(f)

# Convert list to dictionary for quick lookup
avg_gpa_lookup = {prof["name"]: prof["average_gpa"] for prof in
avg_gpa_data}

results = []

# Merge data
for name, data in professors.items():
    avg_gpa = avg_gpa_lookup.get(name)  # Look up from precomputed
file
    reviews = data.get("reviews", [])
    avg_expected = calculate_average_expected_gpa(reviews)

    results.append({
        "name": name,
        "average_gpa": avg_gpa,
        "average_expected_gpa": avg_expected
    })

# Save result
with open('professor_gpa_features.json', 'w') as f:
    json.dump(results, f, indent=2)
```

Generate Sentiment Analysis from reviews

```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

with open("professors.json", "r", encoding="utf-8") as f:
  professors = json.load(f)

analyzer = SentimentIntensityAnalyzer()

sentiment_scores = {}
```

```
for name, data in professors.items():
    reviews = data["reviews"]
    total_score = 0
    count = 0

    for review in reviews:
        text = review["review"]
        sentiment = analyzer.polarity_scores(text)
        total_score += sentiment["compound"]
        count += 1

    if count > 0:
        avg_score = total_score / count
        sentiment_scores[name] = avg_score

with open("professor_sentiment.json", "w", encoding="utf-8") as f:
    json.dump(sentiment_scores, f, indent=2)
```

API call for average rating of each professor - use to train model

```
profs = {}
offset = 0
batch_size = 100

while True:
    response = requests.get(
        f"https://planetterp.com/api/v1/professors?
rtype=professor&limit={batch_size}&offset={offset}"
    )
    profs_data = response.json()


    if not profs_data:
        break

    for prof_data in profs_data:
        if prof_data["average_rating"] == None:
            continue

        name = prof_data["name"]
        to_add = {
            'average_rating': prof_data["average_rating"],
        }
        profs[name] = to_add

    offset += batch_size

# Save the full file after scraping
with open("professors_average_rating.json", "w", encoding="utf-8") as
```

```
f:
    json.dump(profs, f, indent=2)
```

Combine files into one csv for training

```
# Load list of professors with average GPA and expected GPA
with open('professor_gpa_features.json', 'r') as f:
    gpa_data = json.load(f)

# Load sentiment dictionary (name -> sentiment score)
with open('professor_sentiment.json', 'r') as f:
    sentiment_data = json.load(f)

# Load professor average ratings (name -> average_rating)
with open('professors_average_rating.json', 'r') as f:
    rating_data = json.load(f)

combined = []

# Go through each professor in GPA list
for prof in gpa_data:
    name = prof["name"]
    avg_gpa = prof.get("average_gpa")
    avg_expected = prof.get("average_expected_gpa")
    sentiment = sentiment_data.get(name)
    star_rating = rating_data.get(name, {}).get("average_rating")  #
Get star_rating, if available

    # Only include if sentiment exists and star_rating is available
    if sentiment is not None and star_rating is not None:
        combined.append({
            "name": name,
            "average_gpa": avg_gpa,
            "average_expected_gpa": avg_expected,
            "sentiment": sentiment,
            "star_rating": star_rating
        })


# Write to CSV
with open('professor_features.csv', 'w', newline='') as f:
    fieldnames = ["name", "average_gpa", "average_expected_gpa",
"sentiment", "star_rating"]
    writer = csv.DictWriter(f, fieldnames=fieldnames)
    writer.writeheader()
    writer.writerows(combined)
```

Split data into training set and testing set

```
# Load the CSV file into a pandas DataFrame
df = pd.read_csv('professor_features.csv')

#drop missing values
df = df.dropna()

# Features (X) and Target (y)
X = df[["average_gpa", "average_expected_gpa", "sentiment"]]  #
Features
y = df["star_rating"]  # Target (Star rating)

# Split data into training and testing sets (80% training, 20%
testing)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Check the size of the split
print("Training data size:", len(X_train))
print("Testing data size:", len(X_test))
```

```
Training data size: 2926
Testing data size: 732
```

Model Training

```
# Train Linear Regression Model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Train the Random Forest Regression model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Create the KNN regressor model
knn_model = KNeighborsRegressor(n_neighbors=23)

# Train the Support Vector Machine model
svm_model = SVR(kernel='rbf')
svm_model.fit(X_train, y_train)

print("Training Complete!")
```

```
Training Complete!
```

Linear Regression Model Evaulation

```
# Function to perform 10-fold cross-validation for Linear Regression
def evaluate_lr_model(X, y):
    scores = cross_val_score(lr_model, X, y, cv=10,
scoring='neg_mean_squared_error')
```

```
    mse_scores = -scores  # Convert from negative MSE to positive MSE
    r2_scores = cross_val_score(lr_model, X, y, cv=10, scoring='r2')

    print(f"\nEvaluating Linear Regression with 10-fold Cross-
validation:")
    print(f"Mean Squared Error (MSE) (10-fold CV):
{np.mean(mse_scores):.4f}")
    print(f"R2 Score (10-fold CV): {np.mean(r2_scores):.4f}")

# Evaluate Linear Regression model using 10-fold cross-validation
evaluate_lr_model(X_test, y_test)
```

```
Evaluating Linear Regression with 10-fold Cross-validation:
Mean Squared Error (MSE) (10-fold CV): 0.5104
R2 Score (10-fold CV): 0.6100
```

Random Forest Model Evaulation with

```
# Function to perform 10-fold cross-validation for Random Forest
def evaluate_rf_model(X, y):
    scores = cross_val_score(rf_model, X, y, cv=10,
scoring='neg_mean_squared_error')
    mse_scores = -scores  # Convert from negative MSE to positive MSE
    r2_scores = cross_val_score(rf_model, X, y, cv=10, scoring='r2')

    print(f"\nEvaluating Random Forest with 10-fold Cross-
validation:")
    print(f"Mean Squared Error (MSE) (10-fold CV):
{np.mean(mse_scores):.4f}")
    print(f"R2 Score (10-fold CV): {np.mean(r2_scores):.4f}")

# Evaluate Random Forest model using 10-fold cross-validation
evaluate_rf_model(X_test, y_test)
```

```
Evaluating Random Forest with 10-fold Cross-validation:
Mean Squared Error (MSE) (10-fold CV): 0.5397
R2 Score (10-fold CV): 0.5868
```

KNN Model Evaulation

```
knn_cv_scores = cross_val_score(knn_model, X, y, cv=10,
scoring='neg_mean_squared_error')
knn_mean_mse = -knn_cv_scores.mean()  # Convert back from negative MSE
knn_std_mse = knn_cv_scores.std()

print(f"KNN Mean MSE: {knn_mean_mse}")
print(f"KNN MSE Standard Deviation: {knn_std_mse}")
```

```
KNN Mean MSE: 0.44458481401786826
KNN MSE Standard Deviation: 0.07019833510240824
```

Support Vector Machines Model Evaulation

```
# Function to perform 10-fold cross-validation for SVM
def evaluate_svm_model(X, y):
    scores = cross_val_score(svm_model, X, y, cv=10,
scoring='neg_mean_squared_error')
    mse_scores = -scores  # Convert from negative MSE to positive MSE
    r2_scores = cross_val_score(svm_model, X, y, cv=10, scoring='r2')

    print(f"\nEvaluating SVM with 10-fold Cross-validation:")
    print(f"Mean Squared Error (MSE) (10-fold CV):
{np.mean(mse_scores):.4f}")
    print(f"R2 Score (10-fold CV): {np.mean(r2_scores):.4f}")

# Evaluate SVM model using 10-fold cross-validation
evaluate_svm_model(X_test, y_test)
```

```
Evaluating SVM with 10-fold Cross-validation:
Mean Squared Error (MSE) (10-fold CV): 0.5008
R2 Score (10-fold CV): 0.6177
```

Important feature

```
# Get feature importances from the Random Forest model
importances = rf_model.feature_importances_

# Match importances to feature names
feature_names = X.columns
feature_importances = dict(zip(feature_names, importances))

# Print feature importances nicely
print("Feature Importance from Random Forest Regression Model")
for feature, importance in feature_importances.items():
    print(f"{feature}: {importance:.4f}")
```

```
Feature Importance from Random Forest Regression Model
average_gpa: 0.1477
average_expected_gpa: 0.1115
sentiment: 0.7408
```

```
sorted_features = sorted(feature_importances.items(), key=lambda x:
x[1], reverse=True)
names = [item[0] for item in sorted_features]
values = [item[1] for item in sorted_features]

# Plot
```

```python
plt.figure(figsize=(6, 3))
bars = plt.barh(names, values, color='#4CAF50', edgecolor='black')

# Add value labels inside the bars or slightly to the right
for bar in bars:
    plt.text(bar.get_width() + 0.02, bar.get_y() + bar.get_height()/2,
             f'{bar.get_width():.3f}', va='center', fontsize=9)

# Styling
plt.xlabel('Feature Importance', fontsize=12)
plt.title('Feature Importance from Random Forest', fontsize=14,
fontweight='bold')
plt.gca().invert_yaxis()  # Highest importance at the top
plt.grid(axis='x', linestyle='--', alpha=0.7)

# Extend x-axis limit slightly
plt.xlim(0, max(values) + 0.1)

plt.tight_layout()
plt.show()
```